6. The categories must be separate or exclusive to the independent variables.
7. Requires a relatively large sample for predictor variables, for example, a minimum of 50 data samples.
8. The odds ratio is a probability value.

Given vector data $\boldsymbol{x_1}, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_n \in \mathbb{R}^d$ where n is the number of instances and d is the number of features (parameters), and y be a binary outcomes vector. And the vector$\boldsymbol{\theta}$ is the vector of unknown parameters such that $\boldsymbol{x}_i \leftarrow [1, \boldsymbol{x}_i]$ and $\boldsymbol{\theta} \leftarrow [\theta_0, \boldsymbol{\theta}^T]$. From now on, the assumption is that the intercept is included in the vector $\boldsymbol{\theta}$.For every instance $\boldsymbol{x}_i \in \mathbb{R}^d$ where $i = 1,2,\ldots,n$, the outcome is either $y_i = 1$ (positive instance) or $y_i = -1$ (negative instance). The logistic function commonly used to model each positive instance $\boldsymbol{x}_i$with its expected binary outcome is given by

$$E[y_i = 1|\mathbf{x}_i, \boldsymbol{\theta}] = p_i = \frac{e^{\mathbf{x}_i\boldsymbol{\theta}}}{1+e^{\mathbf{x}_i\boldsymbol{\theta}}} = \frac{1}{1+e^{-\mathbf{x}_i\boldsymbol{\theta}}}, \quad (1)$$

where $i = 1,2,3,\ldots,n$.

B. K-Nearest Neighbors (k-NN)

Nearest neighbor search is one of the most popular learning in the field of machine learning and the classification technique introduced by Fix and Hodges. This learning has proven to be a simple and powerful recognition algorithm. Cover and Hart show that decision rules work well given that no explicit knowledge about the data is available. A simple generalization of this method is called the *k*-NN rule, in which new patterns are classified into the class with the most members among the *k*- nearest neighbors. This can be used to obtain a good estimate of Bayes error and the probability of error is asymptotically close to Bayes error.

In the classification technique, the different characteristics in the classification determine the class where the unlabeled data resides with the aim of classifying data based on the closest or neighboring training examples in a particular region. The advantage of this technique is the simplicity of execution and low computation time. For continuous data, it uses the Euclidean distance to calculate its nearest neighbors.

K-nearest neighbor (*k*-NN) is one of the statistical analysis techniques to build the simplest prediction model since it does not require mathematical assumptions and heavy machinery [30]. *K*-NN is a non-parametric supervised learning method and is commonly used for classification [31]. *K*-NN is very popular due to its simplicity and excellent empirical performance. It can handle both binary data and makes no assumptions about the parametric of the decision boundary [32], [33]. This classifier aims to predict the target/class of an observation point based on the closest neighbor k class [34]. In calculating the *k*-NN method, it takes several steps; namely, we choose the value of *k*, then calculate the distance with the distance function from one observation to all other observations and take *k* nearest neighbors as per the calculated distance. After that count the number of observation points in each category among *k* this neighbor. Ultimately, we assign the new observation point to the category with the most neighbors [35] [36].

Given vector data $\boldsymbol{x_1}, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_n \in \mathbb{R}^d$ where n is the number of instances and d is the number of features (parameters), and y be a binary outcomes vector. The goal in classification is to learn a functional model f that allows a reasonable prediction of class label y' for an unknown pattern $\boldsymbol{x}'$. *K*-NN assigns the class label of the majority of the *k*-nearest patterns in data space. For this sake, we have to be able to define a similarity measure in data space. In $\mathbb{R}^d$, it is reasonable to employ the Minkowski metric (p-norm)

$$\left\|\mathbf{x}' - \mathbf{x}_j\right\|^p = \left(\sum_{i=1}^{d}\left|(x_i)' - (x_i)_j\right|^p\right)^{\frac{1}{p}}, \quad (2)$$

which corresponds to the Euclidean distance for $p = 2$. In other data spaces, adequate distance functions have to be chosen, e.g., the Hamming distance in $\mathcal{B}^d$. In the case of binary classification, the label set $Y = \{-1,1\}$ is employed, and *k*-NN is defined as

$$f(\mathbf{x}') = \begin{cases} 1 & \text{if } \sum_{i\in M_k(\mathbf{x}')} y_i \geq 0 \\ -1 & \text{if } \sum_{i\in M_k(\mathbf{x}')} y_i < 0 \end{cases} \quad (3)$$

with neighborhood size k and with the set of indices $M_k(\boldsymbol{x}')$ of the *k*-nearest patterns.

C. Performance Evaluation

In the field of machine learning and computing, evaluating the performance of a classification algorithm is very important. The goal is to measure the performance of an algorithm so that we can consider it in selecting the best algorithm [40]. The input data is grouped into one of two classes in binary classification, which is the simplest and most widely used form. Measuring the performance of the classification model creates a confusion matrix. The output of this confusion matrix can be two or more classes, this research performs a binary classification, so the confusion matrix results are two classes. The confusion matrix aims to compare the classification results of an algorithm with the ground-truth classification results [41].

The representation of the confusion matrix is a matrix table with four combinations of predicted values, and the actual value where the table can be seen in Table I. Suppose there are two classification results, namely positive (labeled 1) and negative (labeled 0), then the four combinations include 1). True Positive (TP) is the amount of positive data that is predicted to be true as positive, 2). False Negative (FN), which is the amount of data that is positive but is predicted to be negative 3). True Negative (TN) where the number of data that is negative and is predicted to be true as negative, and 4). False Negative (FN) is the amount of data that is positive but is predicted to be negative. Next, when a prediction result is a real number, a threshold value of t is needed to distinguish positive and negative classes, after which the confusion matrix can be made [42].

TABLE I
CONFUSION MATRIX

		Predicted Values	
		Positive	**Negative**
Actual Values	**Positive**	TP	FN
	Negative	FP	TN

Furthermore, we use the results of the confusion matrix table to evaluate the performance of the machine learning algorithm for making predictions, namely by calculating the values of precision, recall/sensitivity, specificity, accuracy, and F1-score. For measuring algorithm performance, we could calculate some metrics that are sensitivity or recall (Eq. 3), specificity (Eq. 4), precision (Eq. 5), accuracy (Eq. 6), and F1-score (Eq.7) [43] :

$$\text{sensitivity/recall (true positive rate)} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{specificity (true negative rate)} = \frac{TN}{TN+FP} \tag{4}$$

$$\text{precision (positive predictive value)} = \frac{TP}{TP+FP} \tag{5}$$

$$\text{accuracy} = \frac{TP+TN}{TP+FN+TN+FP} \times 100\% \tag{6}$$

$$\text{F1-score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{7}$$

To add a measure to evaluate the performance of the algorithm, we also use ROC (Receiver Operating Characteristic) analysis which calculates a confusion matrix for all possible threshold values. This ROC curve represents the relationship between the true positive rate or sensitivity (y-axis) and the false-positive rate or 1-specificity (x-axis). After calculating the ROC value, we plot the curve of all ROC values, then calculate the area under the curve, called AUC (Area Under Curve). This AUC-ROC is an area that describes the level of accuracy of the algorithm. The range of AUC-ROC values is between 0 and 1. Generally, the higher the AUC-ROC score, the better a classifier performs for the given task.

D. Dataset

In this research, we use a dataset taken from Kaggle's website about the online advertising of a marketing agency. Then, we process this dataset to predict whether a particular online user will click on an online ad. Therefore, we apply several classification algorithms to predict it. This dataset consists of 1000 observations and 10 features which are: 1). Daily Time Spent on Site, 2). Age, 3). Area Income, 4). Daily Internet Usage, 5). Ad Topic Line, 6). City, 7). Male, 8). Country, 9). Timestamp and 10). Clicked on Ad. The response feature is Clicked on Ad. This feature has two possible outcomes that are 0 and 1 where 0 refers to the case where a user didn't click the advertisement (class 0), while class 1 refers to the scenario where a user clicks the advertisement (class 0). We use features: 'Daily Time Spent on Site' until 'Timestamp' to accurately predict the value 'Clicked on Ad' feature. This research divides data into 67% in training data and 33% in testing data.

E. Methods

There are various methods or classification algorithms in machine learning. Nevertheless, all methods do not have the same accuracy and each algorithm has different accuracy. This research implements two machine learning classification methods on the dataset for predictive analysis and evaluates the performance of each classification algorithm. We use two classification methods or algorithms: logistic regression classifier (LR) and *k*-Nearest Neighbors (*k*-NN) classifier. These methods are very popular in supervised machine learning, so many researchers have good experience with them since they usually have good algorithm performance. Each of these two algorithms has different steps from each other in classifying. A solution has been developed for the classification of numerical data by these two algorithms.

An architecture overview is shown in Fig. 1. At the beginning, we input the dataset we need to classify. In classifying this data set, we used two machine learning classifiers: LR and k-NN. These classifiers were applied to predict if a particular user would click on an online advertisement. Furthermore, to obtain the best classifier method, we evaluate the performance of both classification methods with confusion matrix and several metrics: sensitivity, specificity, precision, accuracy, F1-score, and AUC-ROC.

In the beginning, we input the dataset where the data has been divided into two parts: training data and test data. In classifying this data set, we used two machine learning classifiers: LR and k-NN. These classifiers were applied to predict if a particular user would click on the advertisement. Furthermore, to obtain the best classifier method, we evaluate the performance of both classification methods with several metrics: sensitivity, specificity, precision, accuracy, F1-score, and AUC-ROC.

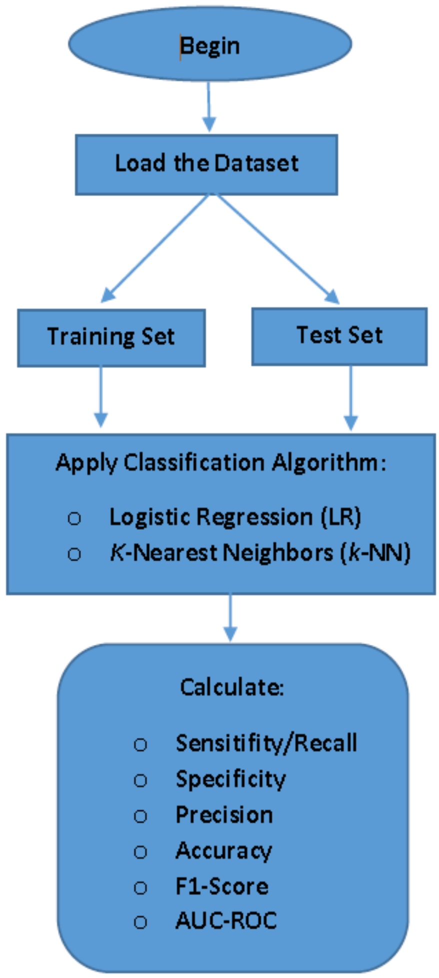


Fig. 1 The Proposed Method Flowchart

III. Results and Discussion

In this section, we first perform and compare the individual logistic regression and *k*-NN classification algorithms on the advertisement dataset. And then, we choose the best classification algorithm of the two classification algorithms based on the calculation of several metrics. We use Python 3.7.3 to perform the simulation results of this research.

First, we apply a logistic regression classifier to the training dataset. Then, we evaluate the performance of both classification methods with a confusion matrix and several metrics: sensitivity, specificity, precision, accuracy, F1-score, and AUC-ROC. And then, we apply a logistic regression classifier to the testing dataset. Then, we also evaluate the performance of both classification methods with a confusion matrix and several metrics: sensitivity, specificity, precision, accuracy, F1-score, and AUC-ROC. Next, we apply *k*-NN algorithm to the training dataset where *k*=2. Then, we also evaluate the performance of both classification methods with a confusion matrix and several metrics: sensitivity, specificity, precision, accuracy, F1-score, and AUC-ROC. And then, we apply *k*-NN algorithm to the testing dataset where *k*=2. Then, we also evaluate the performance of both classification methods with a confusion matrix and several metrics: sensitivity, specificity, precision, accuracy, F1-score, and AUC-ROC.

TABLE II
COMPARISON OF CONFUSION MATRIX RESULTS FOR TRAINING SET

	Logistic Regression		***k*-NN Classifier**	
	Predicted Class		**Predicted Class**	
Actual Class	1	0	1	0
1	312	26	274	64
0	43	289	0	332

The tables are the results of two classification methods or algorithms on online advertising datasets. Table II shows that the logistic regression classifier of training set correctly classifies a total of 312 in class 1 and a total of 289 in class 0. And the *k*-NN algorithm of the training set correctly classifies a total of 274 in class 1 and correctly classifies a total of 332 in class 0.

TABLE III
COMPARISON OF CONFUSION MATRIX RESULTS FOR TESTING SET

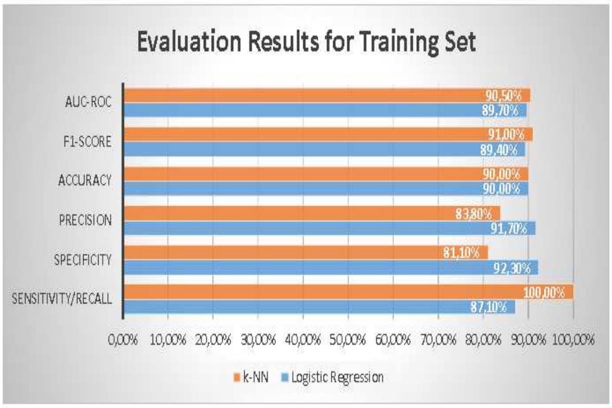
	Logistic Regression		**K-NN Classifier**	
	Predicted Class		**Predicted Class**	
Actual Class	1	0	1	0
1	156	6	95	67
0	25	143	28	140

Table III shows that the logistic regression classifier of the testing set correctly classifies a total of 156 in class 1 and correctly classifies a total of 143 in class 0. Moreover, the *k*-NN algorithm of the testing set correctly classifies a total of 95 in class 1 and correctly classifies a total of 140 in class 0.

Table IV shows several comparisons of the performance evaluation results of two classification methods: the logistic regression classifier and the *k*-NN classifier. First, the comparison of the evaluation results on the training set for the two classifier methods is almost the same value approximation, the values of several metrics, such as sensitivity, F1-score and AUC-ROC in the *k*-NN classifier are greater than the values of the metrics in the logistic regression classifiers, then for the accuracy of the two classifiers the value is the same, in other words, the evaluation results on the training set for the logistic regression classifier method is comparable to the *k*-NN classifier method. Next, the comparison of the evaluation results on the testing set for the two classification methods as a whole show that the value of all evaluation metrics such as sensitivity, sensitivity, precision, accuracy, F1-score and AUC-ROC in the logistic regression classifier method is greater than the *k*-NN classifier method. In other words, the evaluation results on the testing set for the logistic regression classifier method outperformed the *k*-NN classifier method. Overall, the performance of the logistic regression classifier method outperformed both the training set and the testing set as shown in Fig. 2.

TABLE IV
COMPARISON OF LOGISTIC REGRESSION AND *K*-NN EVALUATION RESULTS (%)

Technique	**Evaluation**	**Training**	**Testing**
Logistic Regression	Sensitivity/Recall	87.1	85.1
	Specificity	92.3	96.3
	Precision	91.7	96
	Accuracy	90	91
	F1-Score	89.4	90
	AUC-ROC	89.7	90.7
k-NN	Sensitivity/Recall	100	83.3
	Specificity	81.1	58.6
	Precision	83.8	67.6
	Accuracy	90	71
	F1-Score	91	75
	AUC-ROC	90.5	71



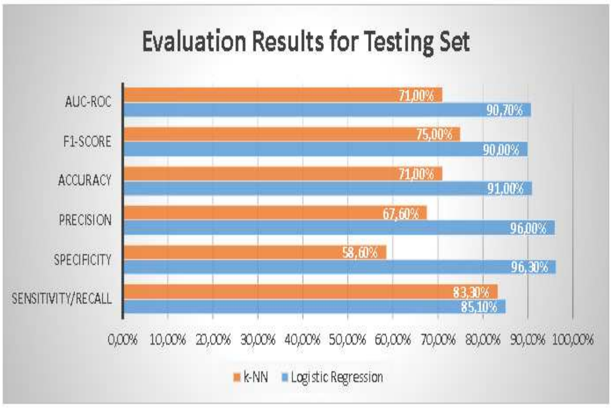


Fig. 2 Comparison of Evaluation Results for Logistic Regression and *k*-NN

IV. CONCLUSIONS

Predicting which customers will click on ads on websites and social media platforms is very important. The company's big goal is to target the right audience to advertise its products on websites and social media platforms. The prediction was implemented by using Logistic Regression and *k*-Nearest Neighbors classifiers. Results showed that the Logistic Regression model outperformed *k*-Nearest Neighbors model. Significant results were obtained from *k*-Nearest Neighbors, too, with slight differences in training sets between the models themselves, depending on the evaluation metrics. Based on the results of this study, it is recommended that further studies need to be carried out in the case of predicting customer ad clicks, such as using other types of machine learning algorithm classification techniques in order to obtain a classification method with the best performance.

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